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Please find below and/or attached an Office communication concerning this application or proceeding.

| Office Action Summary | Application No. 09/833,377 | Applicant(s) CAHILL, NATHAN D. |
|---|---|---|
| | Examiner Wes Tucker | Art Unit 2623 |

*-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --*

**Period for Reply**

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If the period for reply specified above is less than thirty (30) days, a reply within the statutory minimum of thirty (30) days will be considered timely.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

**Status**

1)☒ Responsive to communication(s) filed on 6/13/05.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

**Disposition of Claims**

4)☒ Claim(s) *1-18,20-26,45,46 and 48-54* is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) *1-18,20-26,45,46 and 48-54* is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

**Application Papers**

9)☐ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on *16 May 2005* is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

**Priority under 35 U.S.C. § 119**

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

**Attachment(s)**

1) ☐ Notice of References Cited (PTO-892)

2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)

3) ☐ Information Disclosure Statement(s) (PTO-1449 or PTO/SB/08) Paper No(s)/Mail Date _____.

4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .

5) ☐ Notice of Informal Patent Application (PTO-152)

6) ☐ Other: _____.

## DETAILED ACTION

### *Continued Examination Under 37 CFR 1.114*

A request for continued examination under 37 CFR 1.114, including the fee set forth in 37 CFR 1.17(e), was filed in this application after final rejection. Since this application is eligible for continued examination under 37 CFR 1.114, and the fee set forth in 37 CFR 1.17(e) has been timely paid, the finality of the previous Office action has been withdrawn pursuant to 37 CFR 1.114. Applicant's submission filed on June 13th 2005 has been entered.

### *Response to Amendment*

1. Applicant's response to the last Office Action, filed June 13th, 2005, has been entered and made of record.

2. Applicant has amended claims 1-3,6-8, 13-15, 20, 21, 26, 45, 48,49, 53 and 54. Claims 19, 27-44 and 47 are canceled. Claims 1-18, 20-26, 45, 46 and 48-54 are pending.

3. Applicant's arguments have been fully considered but are not persuasive for at least the following reasons.

103 Rejections

4. Applicant has amended the independent claims to include the limitation of defining a plurality of collections, each of said collections having a plurality of functions

according to a plurality of function parameters and a total number of functions. The previously claimed limitation was simply defining a plurality of functions according to a plurality of function parameters and a total number o functions.

5. Applicant points to the specification for support of this new limitation at page 22, line 28 to page 23, line 5; page 23, line 24 to page 24, line 3; and page 24, lines 12-16. Here as best interpreted the collection of parameters referred to by applicant as a chromosome is basically a set of parameters used in describing a group of functions. It was discussed in the previous rejection that Mitchell teaches the use of defining chromosomes for use in the methods of Snyder and Neves. However as claimed, the collections limitation now listed in claim 1 is comparable to the method disclosed in Neves in section 4. Neves disclose that functions are used in order to determine the best parameters or coefficient variables (x) for use in the function. Therefore the plurality of collections, each of said collections having a plurality of functions according to a plurality of function parameters and a total number of functions as claimed is equivalent to the sets of parameters defined for the functions disclosed by Neves et al.

6. Applicant argues that Neves et al. teaches a fixed number of functions and not where the "total number of functions are altered in randomly selected collections." Examiner submits that Neves discloses a function that uses variable sets that "include different crossover and mutation rates, population sizes and number of generations"

(section 4, 4th paragraph). The emphasis here is on number of generations and population sizes. This is interpreted to read on the total number of functions per collection.

7. Applicant further argues that Neves et al. does not disclose the collections to be selected randomly. Examiner points again to section 4, third paragraph on page 11-31 where Neves states that experimental data was generated using the model function plus a stochastic (or random) factor.

8. The combination of the references to Snyder and Neves is interpreted to disclose the present invention as claimed in light of the newly added limitations. The rejection is therefore maintained.

<u>112 Rejections</u>

9. In view of the amendments and Applicant's remarks the previous 112 rejections are withdrawn.

### ***Objection to the Amendment***

10. The current amendment is objected to because portions of the newly amended claims have not been indicated as newly added. The passage in claim 1, line 13 "in randomly selected said collections" should be underlined in order to indicate newly added claim language.

## *Claim Rejections - 35 USC § 103*

11. The following is a quotation of 35 U.S.C. § 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

12. Claims 1-9, 11-22, and 24-26 are rejected under 35 U.S.C. § 103(a) as being unpatentable over [Snyder90] (W. Snyder et al., *Optimal Thresholding – A New Approach*, Pattern Recognition Letters 11, 1990), in view of [Neves96] (N. Neves et al., *A Study of a Non-Linear Optimization Problem Using a Distributed Genetic Algorithm*, International Conference on Parallel Processing, 1996).

*The following is in regard to Claim 1.* Snyder et al. describe the fitting of a plurality of sub-population functions (a mixture of gaussian probability density functions (pdfs)) to data. See *Section I. Introduction*, paragraphs 1-2 on page 803 of Snyder et al. This fitting technique comprises steps of:

a. Defining a plurality of functions (these functions will be referred to, interchangeably, with *basis functions* henceforth in this document) according to a plurality of function parameters and a total number of functions. See *Section I. Introduction*, paragraphs 2 on page 803 of Snyder et al. Note, in particular, equation (1). Equation (1) consists of a

plurality of gaussians (i.e. $\left\{ \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left[ -\frac{(x-\mu_i)^2}{\sigma_i^2} \right] \right\}_{i=1...d}$ ) which are dependant on the sets parameters. Also defined is a total number of functions *d*.

b. Determining an objective function measuring the fitting error between said modeling function and the data. See the last paragraph on page 803 of Snyder et al. The value *H* defined in equation (4) of Snyder et al. can be considered an objective function measuring the fitting error between said modeling function (*h(x)*)and the data ($h_j$).

c. Comparing said fitting error to stopping criteria to determine if said stopping criteria is satisfied. This is implied by the minimization of the objection function (*H*) discussed in the last paragraph on page 803 of Snyder et al. to the first paragraph on page 804 of Snyder et al. It would be understood by one of ordinary skill in the art that such a minimization would involve a comparison of *H*, which is indicative of the fitting error, to a stopping criteria (i.e. a value considered minimal).

As discussed above, Snyder et al. disclose a method of fitting that is in accordance with claim 1. The fitting technique of Snyder et al. further comprises:

a. The step of altering said plurality of function parameters. This is inherent to the minimization of objective function *H* with respect to the parameter set Θ discussed in the last paragraph of page 803 of Snyder et al. The goal of the procedure is to find the parameter set Θ that minimizes the

objective function. This minimizing set generally involves altering the original set to satisfy the constraints of minimization.

However, Snyder et al. does not teach a fitting method, in accordance with claim 1, further comprising:

b. The step of altering said total number of functions.

c. Repeating:

   i. Generating a modeling function based on said plurality of function parameters.

   ii. Determining an objective function that measures the fitting error between said modeling function and the data.

   iii. Comparing said fitting error to stopping criteria to determine if said stopping criteria is satisfied.

   if, at the comparing step, the fitting error does not satisfy the stopping criteria.

Neves et al. present non-linear least square fitting (which is the essentially the task being performed by the applicant's claimed fitting method and by that of Snyder et al.) as an unconstrained optimization problem. In a manner similar to Snyder et al., Nevės et al. construct the optimization problem in the following way. Find parameter set $X$ such that:

$$\min_{X} \sum_{i=1}^{m} (y(t_i) - f(t_i, X))^2 \qquad (34.1)$$

See paragraph 1 in Section 4, METHODOLOGY, on page II-31 of Neves et al. Their solution to this problem is based on a genetic algorithm. See Abstract and Section 1, INTRODUCTION, of Neves et al.

Snyder also does not explicitly disclose the feature of "defining a plurality of collections, each of said collections having a plurality of functions..." However as claimed, the collections limitation now listed in claim 1 is comparable to the method disclosed in Neves in section 4. Neves disclose that functions are used in order to determine the best parameters or coefficient variables (x) for use in the function. Therefore the plurality of collections, each of said collections having a plurality of functions according to a plurality of function parameters and a total number of functions as claimed is equivalent to the sets of parameters defined for the functions disclosed by Neves et al. Therefore it would have bee obvious to one of ordinary skill in the art at the time of invention to define a plurality of collections as taught by Neves in order to analyze each collection based on the parameters selected for the functions in the method of Snyder.

With regard to claim 2, by virtue of the genetic algorithm used, Neves et al. teach a method of non-linear least squares fitting comprising:

b. The step of altering said total number of functions. Refer to section 2, BACKGROUND. The discussion therein relates to the theoretical basis of genetic algorithms. As discussed there (last paragraph of Neves et al.'s

BACKGROUND), genetic algorithms begin with an initial population New individuals (states in the search space) are introduced and individuals of the current or prior generations are eliminated based on their fitness. It should be understood that, with regard to the methodology proposed in section 4 of Neves et al., the search space is the space of all potential parameter sets *X*. Each of these parameter sets corresponds to a function *f (t,X)* in a bijective manner. Therefore, as the number of parameter set candidates changes through successive generations, so to does the total number of corresponding functions.

c. Repeating:.

  i. Determining an objective function that measures the fitting error between said modeling function and the data.

  ii. Comparing said fitting error to stopping criteria to determine if said stopping criteria is satisfied.

if, at the comparing step, the fitting error does not satisfy the stopping criteria. Again, this is inherent to the genetic algorithm of Neves et al. During each generation of the algorithm,

parameter sets *X* are generated and the functions *f(t,X)*are evaluated. The objective function (e.g. 34.1 above) is evaluated (where it is clear that 34.1 measures the fitting error). The algorithm continues until it converges to a global optimum (see section 2, BACKGROUND, of Neves et al.).

Note from the preceding discussion that both Neves et al. and Snyder attempt to solve the same problem, that is, minimizing the sum of the squared errors between the modeling function and the input data. It would be well within the capabilities of one of ordinary skill in the art to utilize a genetic algorithm of Neves et al. to find the global minimum of the objective function *H* in the fitting technique of Snyder et al., particularly since Neves et al. have demonstrated the use the algorithm in minimizing the sum of the squared errors between the modeling function and the input data. (Note the objective functions of Neves et al. and Snyder et al. are the same). The advantages of applying genetic algorithms to optimization problems, involving the minimization of the sum of the squared errors between the modeling function and the input data, are, among other things, that these algorithms converge, unsupervised, to a *global* minimum, easily accommodate a variety of constraints, are self-adaptive (in the sense that bad solutions are eliminated without intervention) and are relatively insensitive to initial parameters such as population size, when compared to other optimization methods. Given these advantages of genetic algorithms and their demonstrated applicability to optimization problems involving the minimization of the sum of the squared errors between the modeling function and the input data, it would have been obvious to one of ordinary skill in the art, at the time of the applicant's claimed invention, to use the genetic algorithm of Neves et al. to minimize the objective function (fitting error) of the fitting technique taught by Snyder et al. In doing so, one would obtain a method of fitting that conforms to all limitations of claim 2.

The discussion of the newly added limitations of claim 1 applies to the other independent claims adding the same subject matter as well. With regard to the amendments in subsequent claims that simply reflect the newly added collections limitation, the responses in regard to claim 1 apply as well. The rejection of the remaining claims has been repeated from previous office actions below.

With regard to the amended claims 8, 21 and 49 the previous discussion applies. As shown, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 7. In genetic algorithms, mutation and crossover are standard operations used to evolve the data toward optimization. See, for example, Fig. 1 of Neves et al. and column1, last paragraph on page II-31. In this way, the teachings of Snyder et al. and Neves et al., when combined in the manner discussed above, produce a fitting method in accordance with claim 8. Claim 8 has been amended to be more specific in by the evolving includes crossover followed by mutation. It is submitted that these operations may be employed in any kind of order and that Neves discloses as cited above a crossover rate followed by a mutation rate.

*The following is in regard to Claim 3.* As shown above, Snyder et al. show a method of fitting in accordance with claim 1. Snyder et al. further disclose determining an optimum threshold that delineates said plurality of functions. See the second paragraph of Section I. *Introduction* on page 803 of Snyder et al. Note in particular

equation (2). Therefore, the method put forth in applicant's claim 3 is anticipated by the teachings of Snyder et al.

*The following is in regard to Claim 4.* As just shown, Snyder et al. teach a method of fitting in accordance with claim 3. The optimum threshold, discussed above, minimizes the overall probability of error (i.e. the likelihood of misclassification of the data). See paragraph 2 on page 803 of Snyder et al. Therefore, the method put forth in applicant's claim 4 is anticipated by the teachings of Snyder et al.

*The following is in regard to Claim 5.* As shown above, Snyder et al. teach a method of fitting in accordance with claim 3. As described in paragraph 1 on page 803 of Snyder et al., the optimum threshold separates or segments the data according to the various modes (relative maxima) present in the data. Therefore, the method put forth in applicant's claim 5 is anticipated by the teachings of Snyder et al.

*The following is in regard to Claim 6.* As shown above, Snyder et al. teach a method of fitting in accordance with claim 1. Furthermore, Snyder et al. suggest (see equation (5)) that the modeling function is expressible as a vector[1] whose elements are the plurality of parameters (i.e. means, variances, and a priori probabilities) associated

[1] Technically, equation (5) of Snyder expresses the parameter set representing the modeling function as a set. Clearly, this set can be trivially expressed as a vector. While a set and vector are mathematically different, for the purposes of the algorithm disclosed by Snyder et al. and the method proposed by the applicant, they both represent collections of data and, therefore, can be treated as the same.

with the said plurality of gaussians. In this manner, the teachings of Snyder et al. anticipate the method of fitting proposed by the applicant in claim 6.

*The following is in regard to Claim 9.* As shown above, Snyder et al. teach a method of fitting in accordance with claim 1. As mentioned above, with regard to claim 1, Snyder et al. teach that the basis functions are normal gaussian distributions, with means and standard deviations, *i=1...d.* See equation (1) of Snyder et al. Furthermore, the parameter set Θ associated with these basis functions consists of the means and standard deviations, *i=1...d.* See equation (5) of Snyder et al.

*The following is in regard to Claim 11.* As shown above, Snyder et al. teach a method of fitting in accordance with claim 1. The input data being fitted is in the form of a mutimodal histogram. See paragraph 1 on page 803 of Snyder et al. Therefore, the method of fitting proposed by the applicant in claim 11 is anticipated by the teachings of Snyder et al.

*The following is in regard to Claim 12.* As shown above, Snyder et al. teach a method in accordance with claim 1. As mentioned by Snyder et al., the objective function *H* is minimized with respect to the parameter set (Θ). See the last paragraph on page 803 of Snyder et al. to the first paragraph on page 804 of Snyder et al. As discussed above, with regard to claim 1, this minimization implies that a stopping criteria

(e.g. $\frac{\partial H}{\partial \Theta} = 0$ – see paragraph 1 on page 804 of Snyder et al.) be compared to the objective function.

The objective function *H* can be considered a fitness function, in a similar vein as the applicant, since it is a function providing a measure of the goodness-of-fit of the model to the input data. In this way, the method put forth by the applicant in claim 12 is anticipated by the teachings of Snyder et al.

*The following is in regard to Claim 13.* As shown above, Snyder et al. teach a method in accordance with claim 12. Again, with regard to Snyder et al.'s fitting technique, the optimization involves the minimization of the objective function *H* with respect to the set of parameters Θ. As mentioned above, with regard to claim 12, the objective function can be considered a fitness function. Furthermore, it is clear from the form of *H*, shown in equation (4) of Snyder et al., that *H* is a measure of the magnitude of the fit error between the modeling function and the input data. In fact, to minimize *H* is to minimize this error, and vice versa. In this sense, the fitting technique taught by Snyder et al., optimizes the fitting function *H* by minimizing the fit error between the modeling function and the input data. Given this, it is clear that the method proposed by the applicant in claim 13 is anticipated by the teachings of Snyder et al.

*The following is in regard to Claims 14, 16-19, 22, and 24-26.* These claims recite substantially the same limitations as claims 1, 3-6, 9, and 11-13, respectively.

Therefore, with regard to claims 14, 16-19, 22, and 24-26, remarks analogous to those presented above with regard to claims 1, 3-6, 9, and 11-13 are, respectively, applicable.

*The following is in regard to Claim 2, 6, 15, and 19.* Recall that, in the previous Office Action, Claim 6 was interpreted as: "The method of Claim 1, wherein said *modeling function* is defined as a vector representation of said plurality of function parameters". See paragraph 13 on page 5 of the previous Office Action. The "modeling function" of the previous Office Action and the "model" of amended Claim 2 are synonymous. The discussion in the previous Office Action regarding Claim 6, therefore, addresses all limitations of amended Claim 2. For the sake of brevity, that discussion will be not be repeated here. Please refer to paragraph 6 on page 9 of the previous Office Action.

The rejections of the current Claims 15 and 19 follow similarly. Please refer additionally to paragraph 32 on page 11 of the previous Office Action.

*The following is in regard to Claims 3-9, 11-13, 16-22, and 24-26.* The Applicant has not amended these claims. The rejections of Claims 3-9, 11-13, 16-22, and 24-26 follow directly from the arguments presented in the previous Office related to these claims, as well as the discussions above relating to the claims upon which they depend. For the sake of brevity, those arguments will be omitted here. Please refer to the appropriate sections of the previous Office Action.

13. Claims 10 and 23 are rejected under 35 U.S.C. § 103(a) as being unpatentable over [Snyder90], in view of [Neves96], in further view of [Levine99] (D. Levine, *Statistics For Managers Using Microsoft Excel: Chapter 14 – Multiple Regression Models*, Prentice-Hall, 1999).

*The following is in regard to Claims 10 and 23.* As discussed above an the previous Office Action, [Snyder90] and [Neves96] can be combined to yield a method in accordance with Claim 1. Neither [Snyder90] nor [Neves96], however, suggest utilizing a statistical *F*-test to evaluate the relative contribution of each of the plurality of functions in comparison of the fitting error and the data.

As discussed in the previous Office Action (page 19, paragraph 54), the *F*-test is a well-known statistical test used to determine whether two populations have equal variances. It is frequently used to analyze the goodness-of-fit of linear regression models. (Least-squares fitting, such as performed in the applicant's claimed fitting method and discussed by both [Snyder90] and [Neves96], is a form of linear regression). A common application of the *F*-test is to analyze the contribution of an independent variable to the goodness-of-fit of a model that depends on multiple independent variables. See [Levine99] slides 14-18 to 14-23.

Note that the mixture models discussed by [Snyder90] (and those used in the applicant's fitting method) represent models (i.e. the modeling functions) that depend on multiple independent variables (i.e. the basis functions). Consequently, the *F*-test can

be used to analyze the modeling functions of [Snyder90] in the manner described above. It would be straightforward for one of ordinary skill in the art to incorporate the *F*-test into the objective function of Snyder, thereby providing an additional measure of the goodness-of-fit of the modeling function to the input data. Clearly, one is motivated to do so to provide a more precise measure of the goodness-of-fit of the modeling function to the input data, in addition to providing a measure of the optimal number of basis functions to use in the modeling function[2]. Given the straightforwardness of such a modification and its clear advantages, it would have been obvious to one of ordinary skill in the art, at the time of the applicant's claimed invention, to incorporate the *F*-test into the objective function of the fitting technique, obtained by combining [Snyder90] and [Neves96]. In doing so, one would obtain a fitting method, in accordance with Claim 1, further comprising using an *F*-test to evaluate the relative contribution of each of the basis functions when comparing the objective function to the stopping criteria. Such a fitting method conforms to all limitations of Claim 10.

The rejection of Claim 23 follows similarly.

14. Claims 45-50 and 52-54 are rejected under 35 U.S.C. § 103(a) as being unpatentable over [Snyder90], in view of [Neves96], in further view of [Mitchell94] (M. Mitchell and S. Forrest, *Genetic Algorithms and Artificial Life*, Artificial Life Vol. 1(3), 1994).

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2 Since the *F*-test provides a measure of the contribution of a basis function to the goodness-of-fit of the modeling function, modeling functions with extraneous basis functions (i.e. *basis functions* [see the previous Office Action] that make little contribution to the goodness-of-fit) can be considered less optimal.

*The following is in regard to Claim 45.* As shown in [Snyder90] and in the previous Office Action, [Snyder90] discloses a method for specifying thresholds (i.e. *optimal thresholding* – [Snyder90] Abstract) for segmenting a digital image. The method of [Snyder90] comprises:

(45.a.) Producing a histogram of the image ([Snyder90] Section 1, paragraph 1, sentence 1).

(45.b.) Defining a mixture model (e.g. Gaussian mixture model, *h*(*x*) – equation (1) of [Snyder90]) as a combination (e.g. a weighted sum – cf. [Snyder90] equation (1)) of a plurality (e.g. *d* – see [Snyder90] Section 1, paragraph 2, sentence 1) of subpopulations (e.g. Gaussians $\left\{\frac{1}{\sqrt{2\pi\sigma_i}}\exp\left[-\frac{(x-\mu_i)^2}{\sigma_i^2}\right]\right\}_{i=1\ldots d}$ ), wherein each subpopulation is a function defined according to a plurality of function parameters (i.e. means and variances ). Refer, generally, to [Snyder90] equation (1).

($45.c_{Snyder}.$) Defining a vector (e.g. equation (5)) encoding the mixture model, wherein elements of the vector encode the plurality of function parameters of the plurality of sub-populations. See the last paragraph of the right column on page 803of [Snyder90].

($45.d_{Snyder}.$) A "generation" is formed of a plurality of vectors, at each iteration of the algorithm. [Snyder90] proposes two approaches to optimization:

gradient descent ([Snyder90], Section 2) and simulated tree-annealing ([Snyder90], Section 3). In the first approach the generation is a collection of vectors at iteration *k* (cf. equation (6) in [Snyder90], Section 2, paragraph 1). According to the second approach, the generation comprises the vectors (solutions) *x* and *y* in each iteration of the algorithm (cf. [Snyder90] page 806, left column, paragraphs 1 and 2 (*Steps 1-2*), Section 3.1, and paragraph 1 of Section 3.2).

(45.$e_{Snyder}$.) For each vector in the "generation" (i.e. for each iteration):

1. Determining the fitting error (e.g. objective function, *H* – [Snyder90] equation (4)) between the mixture model (e.g. *h*(*x*) – [Snyder90] equation (4)) and the histogram data (e.g. $h_j$ – [Snyder90] equation (4)). Refer to equation (4) of [Snyder90], paragraph 1 of Section 2, and second to last paragraph in the right column of page 805.
2. Determining a measure of relative contributions (e.g. $P_i$ – cf. equations (1) and (3) of [Snyder90]) of the individual sub-populations (e.g. the aforementioned Gaussians) defined by each vector. The optimal values for the weights $P_i$ are determined along with the optimal values for the collection Gaussian parameters (cf. last two paragraphs in Section 1 of [Snyder90]).

3. Determining a fitness value (e.g. objective function, $H$ – see equation (4)) based on the fitting error (e.g. the square error $\Sigma[\tilde{h}_j - h(x_j,\Theta)]^2$ – see equation (4) of [Snyder90]). Note that this value is also based, *inter alia*, on said measure of relative contributions ($P_i$). To see this notice that $h(x,\Theta)$ is a function of $\Theta$, which includes the parameters $P_i$ (cf. [Snyder90] equations (1), (4), and (5)). Clearly then, the fitness value, $H(x)$, is dependent on the relative contributions $P_i$.
4. Comparing said fitness values to a stopping criterion. Optimization methods generally require some predefined stopping criteria for evaluating the convergence to a solution. A stopping criterion is, therefore, inherent to the method of [Snyder90]. Gradient descent typically terminates when the error becomes sufficiently small and the algorithm has approximately converged to a solution. In simulated annealing, the algorithm terminates when the temperature ($T$ – see [Snyder90] page 806, left column, *Step 2* and Section 3.3) cools to some predefined value, or when some other stopping criterion has been met. Official Notice is taken.

($45.f_{Snyder.}$) 1. Altering the vectors (cf. [Snyder90] equation (6), *Step 2* in the left column of page 806, and *Steps 3-4* in the right column of page 806).

As discussed above, the method [Snyder90] iterates until it converges to a solution (i.e. the until the stopping criterion (or criteria) is satisfied) or has exhausted the entire search space (*S* – see the second to last paragraph in the right column of page 805 of [Snyder90]). In other words, [Snyder90] further compises:

2. Repeating said first and second defining (i.e. steps (45.b.)-(45.$c_{Snyder}$.) above) , and forming steps (i.e. step (45.$d_{Snyder}$.)), if none of said fitness values satisfies said stopping criteria.

(45.g.) Specifying at least a first threshold value delineating said sub-populations in the mixture model (cf. [Snyder90] Section 1, paragraphs 1-2) if at least one of said fitness values satisfies said stopping criteria. As discussed above, the algorithm converges to an optimal vector (i.e. in *S* having a "fitness value satisfying the stopping criteria"). That represents the Gaussian mixture which fits the given histogram optimally. [Snyder90] uses this mixture model to derive the optimal thresholds for segmenting the various modes of the given histogram.

Notice that [Snyder90] uses simulated annealing to achieve optimization, as opposed to a genetic algorithm. Therefore, the search space is not encoded as set of *chromosomes*.

As discussed in the previous Office Action, [Neves96] suggest the application of genetic algorithms to optimization problems which involve the least-squares fitting a

model to a set of empirical data. Such optimization problems are analogous to that of [Snyder90] (cf. paragraphs 1 and 4 in Section 4 of [Neves96]; note in particular the similarity of the first and third equations to equation (4) of [Snyder90]). Specifically, both [Snyder90] and [Neves96] attempt to find a set of parameters (i.e. $X$ in [Neves96] and □ in [Snyder90]) that minimize the square error between the model (i.e. $f$ in [Neves96] and $h$ in [Snyder90]) and the empirical data (i.e. cal data (i.e. $y(t_i)$ in [Neves96] and $h_j$ in [Snyder90]). Genetic algorithms (GA) and simulated annealing (SA) are competing heuristics in the field of optimizations, and both have been used to solve the same types of problems. Simulated annealing algorithms, however, are generally more difficult to implement than genetic algorithms. The algorithm must be tailored specifically to the given application in order to ensure convergence (cf. paragraph 1, lines 13-18 in Section 2 of [Neves96], and paragraph 2, sentences 1-2 in Section 2 of [Neves96]). Other advantages of GA were discussed in paragraph 43 on pages 16-17 of the previous Office Action. Therefore, given these advantages and the teachings of [Neves96], it would have been obvious to one of ordinary skill in the art, at the time of the Applicant's claimed invention, to use GA to determine the optimal Gaussian mixture (i.e. the optimal parameter set $\Theta$) in the optimal thresholding method of [Snyder90].

Aside from discussing the notion of "generations" within the context of genetic algorithms ([Neves96] Section 2, paragraph 2), [Neves96] does not provide a detailed description of these algorithms. It is well known, however, that GA act on populations of chromosomes and the complete set of chromosomes, otherwise known as a *genome*. The genome is analogous to the Applicant's "master chromosome", in the sense that it

encodes the complete array of "genetic" information (*genes*) contained in all chromosomes. Chromosomes and genomes are essential structures in genetic algorithms. [Mitchell94] shows this, for example, on page 2 (paragraph 3), page 7 (paragraph 1), and page 9 (paragraph 2). A general overview of GA appears in Section 2 of [Mitchell94]. Notice from that discussion that GA comprises the following steps:

($45.c_{Mitchell.}$) Defining chromosomes that encode candidate solutions to a problem (cf. *Step 1* and *Step 3* in [Mitchell94], Section 2).

($45.d_{Mitchell.}$) A generation is formed of a plurality of chromosomes (cf. *Step 1* and *Step 3* in [Mitchell94], Section 2; see also line 3 on page 3 of [Mitchell94]). As discussed above, the *genes* ([Mitchell94], Section 2, lines 8-9) of these chromosomes constitute a genome, or "master chromosome".

($45.e_{Mitchell.}$) For each chromosome in the generation:

1. Determining the fitness of each chromosome.

($45.f_{Mitchell.}$)

1. Altering the chromosomes (cf. *Step 3* in [Mitchell94], Section 2).
2. Repeat the defining step ($45.c_{Mitchell.}$), the forming step ($45.d_{Mitchell.}$), and the fitness determination step ($45.e_{Mitchell.}$). Clearly, the algorithm does not iterate *ad infinitum*. Therefore, the GA must entail some stopping criterion, which indicates when the said repeating should cease.

[Mitchell94] suggests the application of GA to optimization problems ([Mitchell94], page 3, paragraph 2). Therefore, it would have been obvious to one of ordinary skill in the art,

at the time of the Applicant's claimed invention, to apply GA to optimization problems and, more particularly, to the optimization problems of [Snyder90] and [Neves96]. Notice the similarities between (45.$c_{Snyder.}$)-(45.$f_{Snyder.}$) of [Snyder90] and (45.$c_{Mitchell.}$)-(45.$f_{Mitchell.}$). Clearly, a GA implementation of steps (45.$c_{Snyder.}$)-(45.$f_{Snyder.}$) of [Snyder90] would comprise, in addition to steps (45.a.)-(45.b.) and (45.g.):

(45.c.) Defining a chromosome to be a vector encoding of the mixture model, wherein elements of the vector encode the plurality of function parameters of the plurality of sub-populations.

(45.d.) Forming a generation, wherein a generation comprises of a plurality of chromosomes and a genome.

(45.e.) For each vector in the "generation" (i.e. for each iteration):

1. Determining the fitting error between the mixture model and the histogram data.
2. Determining a measure of relative contributions of the individual sub-populations defined by the chromosomes.
3. Determining a fitness value based on the fitting error and the measure of relative contribution.
4. Comparing said fitness values to a stopping criterion.

(45.f.)
1. Altering the chromosomes.
2. Repeating said first and second defining, and forming steps, if none of said fitness values satisfies said stopping criteria.

Similar arguments apply for Claim 54.

*The following is in regard to Claim 47.* The limitations of Claim 47 were treated above with respect to amended Claim 2. Please refer to that discussion and the associated sections of the previous Office Action.

*The following is in regard to Claims 46, 48, 49, 52, and 53.* These claims recite substantially the same limitations as Claims 4, 8, 12, and 13, respectively. These limitations have been treated above and in the previous Office Action. For the sake of brevity, that discussion will not be repeated here. Please refer to the following sections of the previous Office Action: paragraph 25 on page 9, paragraph 40 on page 14, and paragraphs 30-31 on page 10.

*The following is in regard to Claim 45.* As discussed above, in the method of [Snyder90], a plurality (mixture) of Gaussians (normal distributions) are fit to the histogram data. The parameter set $\Theta$ includes the means, $\mu_i$, and standard deviations, $\sigma_i$ (cf. equation (5) of [Snyder90]).

15. Claims 51 are rejected under 35 U.S.C. § 103(a) as being unpatentable over [Snyder90], [Neves96], and [Mitchell94], in further view of [Levine99].

*The following is in regard to Claim 51.* The limitations of Claim 51 were treated above and in the previous Office Action. Please refer to the discussion above and in paragraphs 53-55 on pages 19-20 of the previous Office Action.

### *Conclusion*

16. Any inquiry concerning this communication or earlier communications from the examiner should be directed to Wes Tucker whose telephone number is 571-272-7427. The examiner can normally be reached on 9AM-5PM.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Jingge Wu can be reached on 571-272-7429. The fax phone number for the organization where this application or proceeding is assigned is 703-872-9306.

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Wes Tucker

8-24-05

VIKKRAM BALI
PRIMARY EXAMINER